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(54) **METHOD AND APPARATUS FOR CONTINUAL FEW-SHOT LEARNING WITHOUT FORGETTING**

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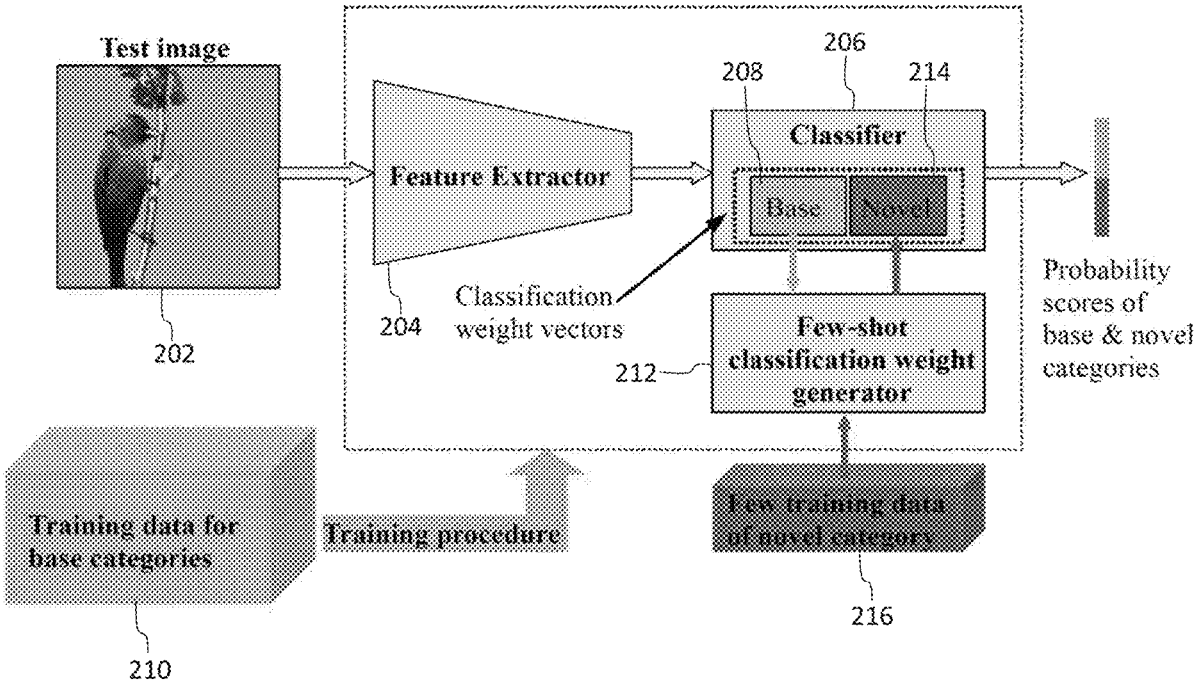
(57) **ABSTRACT**

Methods and apparatuses are provided for continual few-shot learning. A model for a base task is generated with base classification weights for base classes of the base task. A series of novel tasks is sequentially received. Upon receiving each novel task in the series of novel tasks, the model is updated with novel classification weights for novel classes of the respective novel task. The novel classification weights are generated by a weight generator based on one or more of the base classification weights and, when one or more other novel tasks in the series are previously received, one or more other novel classification weights for novel classes of the one or more other novel tasks. Additionally, for each novel task, a first set of samples of the respective novel task are classified into the novel classes using the updated model.




Training task 1 102
Support set 108
K=2
N=3
Query set 114
Training task 2 104
Support set 110
Query set 116
Test task 1 106
Support set 112
Query set 118

FIG. 1

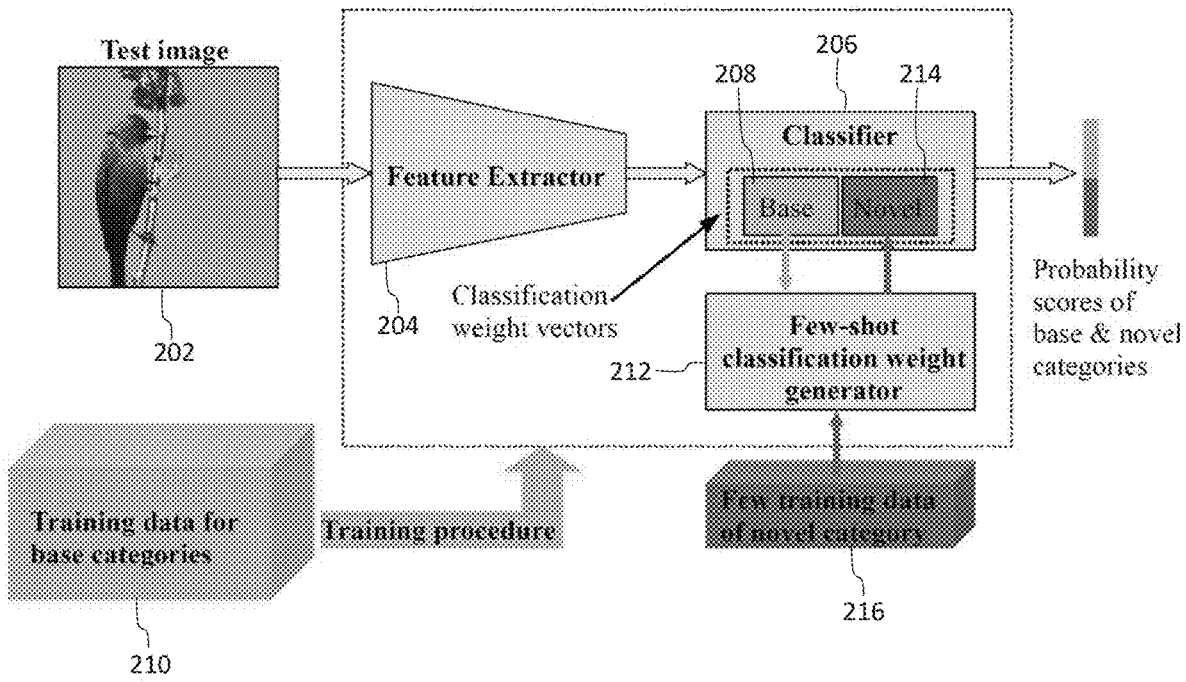

Test image
202
Feature Extractor
204
206
208
214
Classifier
Base
Novel
Classification weight vectors
Few-shot classification weight generator
212
Probability scores of base & novel categories
Training data for base categories
210
Training procedure
Few training data of novel category
216

FIG. 2

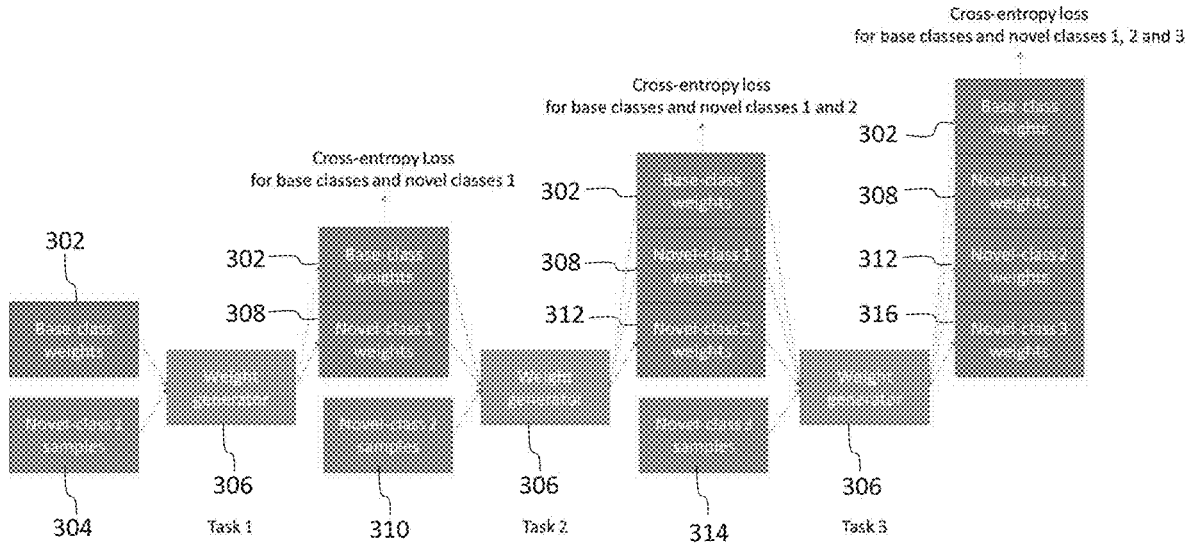
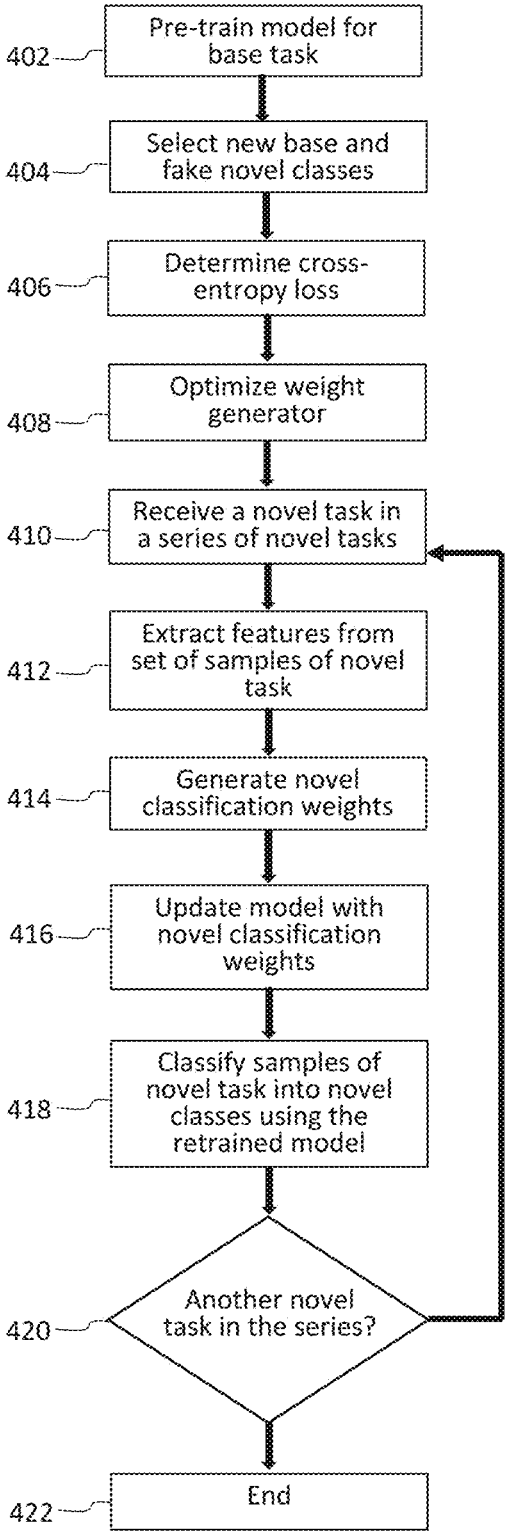

Cross-entropy loss
for base classes and novel classes 1, 2 and 3
Cross-entropy loss
for base classes and novel classes 1 and 2
Cross-entropy Loss
for base classes and novel classes 1
302
308
312
316
306
304
310
314
Task 1
Task 2
Task 3

FIG. 3

FIG. 4


402
Pre-train model for base task
404
Select new base and fake novel classes
406
Determine cross-entropy loss
408
Optimize weight generator
410
Receive a novel task in a series of novel tasks
412
Extract features from set of samples of novel task
414
Generate novel classification weights
416
Update model with novel classification weights
418
Classify samples of novel task into novel classes using the retrained model
420
Another novel task in the series?
422
End

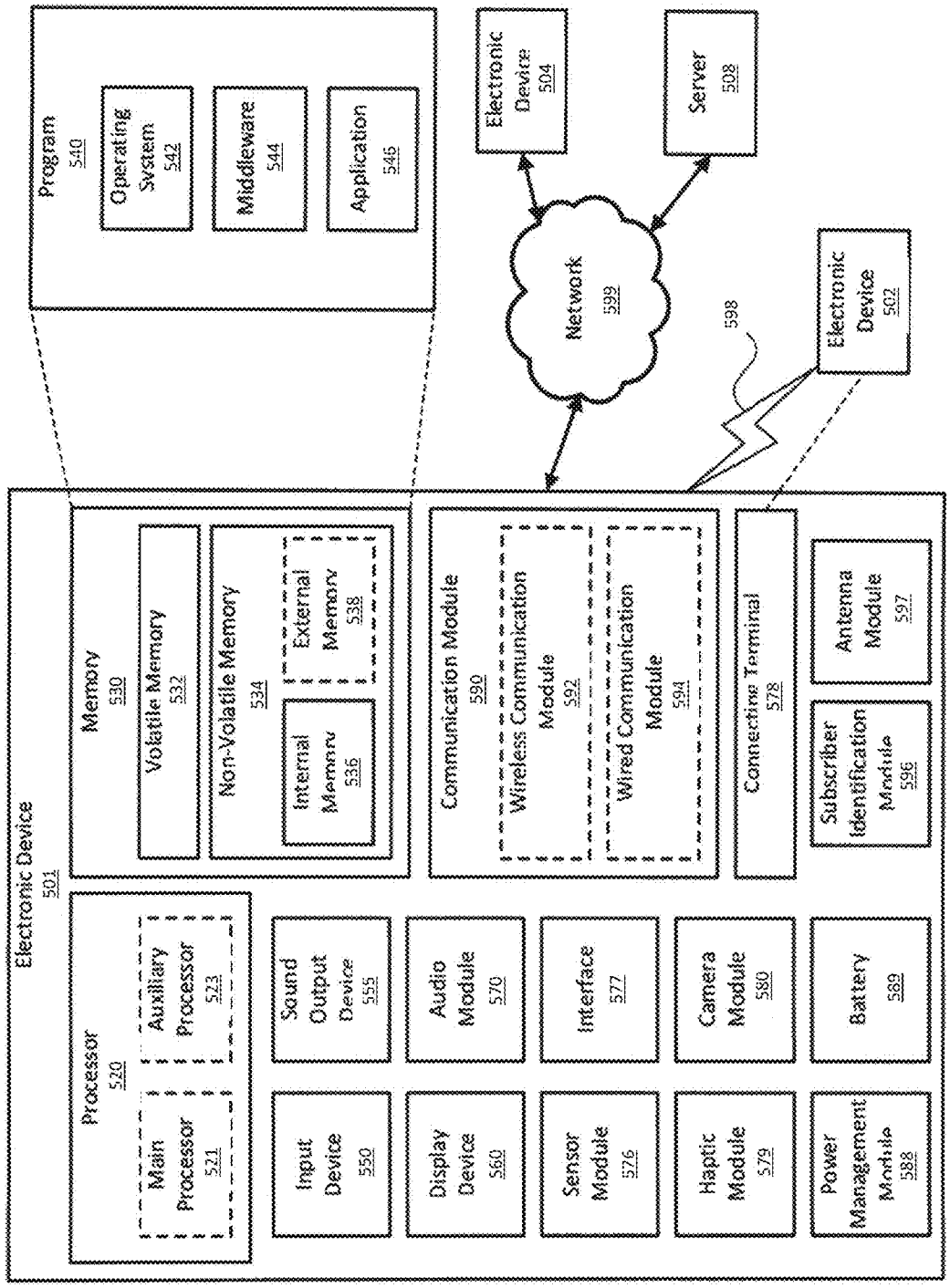

500
Electronic Device
501
Processor
520
Main Processor
521
Auxiliary Processor
523
Memory
530
Volatile Memory
532
Non-Volatile Memory
534
Internal Memory
536
External Memory
538
Input Device
550
Sound Output Device
555
Display Device
560
Audio Module
570
Sensor Module
576
Interface
577
Haptic Module
579
Camera Module
580
Power Management Module
588
Battery
589
Communication Module
590
Wireless Communication Module
592
Wired Communication Module
594
Connecting Terminal
578
Subscriber Identification Module
596
Antenna Module
597
Program
540
Operating System
542
Middleware
544
Application
546
Electronic Device
504
Server
508
Network
599
598
Electronic Device
502

FIG. 5

METHOD AND APPARATUS FOR CONTINUAL FEW-SHOT LEARNING WITHOUT FORGETTING

PRIORITY

[0001] This application is based on and claims priority under 35 U.S.C. § 119(e) to a U.S. Provisional Patent application filed on Aug. 27, 2020 in the United States Patent and Trademark Office (USPTO) and assigned Ser. No. 63/071,067, the contents of which are incorporated herein by reference.

FIELD

[0002] The present disclosure relates generally to machine learning methods, and more particularly, to a method and an apparatus for continual few-shot learning.

BACKGROUND

[0003] Within the field of machine learning, it may be difficult to accrue enough data to increase the accuracy of models. In limited-data scenarios, few-shot learning algorithms have been employed to discover patterns in data and make inferences. This technique is commonly utilized in the field of computer vision, where photos are categorized or classified.

[0004] In a few-shot learning task, where N is the number of classes and K is the number of samples (or images) in each class, a small training set D is provided. The size of a training set is $|D|=N \cdot K$.

[0005] A base training set D_0 may be utilized to learn transferable knowledge for improved few-shot learning. Base training set D_0 contains a large number of labeled samples from a large number of classes. However, the classes in base training set D_0 are not identical to the classes in training set D. Accordingly, traditional few-shot learning trains a model with a small amount of training data or samples, without utilizing the base classes.

[0006] An episode refers to a training and testing pair of one few-shot learning task. FIG. **1** is a diagram illustrating an episodic few-shot learning method. A first training task **102**, a second training task **104**, and a first test task **106** each include a respective support set **108**, **110**, and **112**, having three classes (N=3) and two samples (images) per class (K=2). The first training task **102**, the second training task **104**, and the first test task **106** each also include and a respective query set **114**, **116**, and **118**, having three samples (images). The classes differ in each of the first training task, the second training task, and the first test task.

[0007] Both metric-based and gradient-based training algorithms have been developed on top of the episodic learning framework. For example, self-supervision loss may be added to a feature extractor training procedure to enable robust semantic feature learning and to improve few-shot classification. Additionally, a Wasserstein-based method may be added to better align the distribution of features with that of considered classes. However, as described above, traditional few-shot learning does not take into account the base classes used in training.

[0008] Few-shot learning without forgetting base classes has been developed to classify novel classes when only a few labeled samples are provided for the novel classes, while also preserving the capability to classify base classes upon which the feature embedding network is trained. For example, the feature embedding network and classification weights for base classes are pre-trained by regular supervised learning and are fixed afterwards.

[0009] FIG. **2** is a diagram illustrating few-shot learning without forgetting base classes, which focuses on generating the classification weights for novel classes. A sample or test image **202** is provided to a feature extractor **204**, which outputs features of the sample to a classifier **206**. The classifier **206** obtains base classification weights **208** from training data for base classes **210**. A few-shot classification weight generator **212** generates novel classification weights **214** for the limited training data of a novel category **216**, and provides the novel classification weights **214** to the classifier **206**.

[0010] More specifically, with respect to the few-shot classification weight generator **212**, a weight imprinting method computes prototypes of novel classes from a pre-trained feature embedding network and uses them as the classification weights for novel classes. Also, generation of classification weights **214** for novel classes is learned by a weight generator that takes novel class prototypes **216** and the classification weights **208** for base classes as inputs, utilizing an attention-based mechanism to exploit the relation between base classes and novel classes in the generation of novel classification weights **214**.

[0011] Based on the base classification weights **208** and novel classification weights **214**, the classifier outputs a probability of base and novel classes for the sample **202**.

[0012] Further, the novel classification weights may be trained by a gradient-based optimization process using the cross-entropy loss from a few labeled samples of the novel classes until they converge. Since the loss for training novel classification weights is computed only with the samples of the novel classes, a forgetting issue for base classes may arise. To prevent this, an attention-based regularization method is applied. The regularization loss is provided by an attention attractor network. The attention attractor network generates attractor vectors using the base classification weights, and the regularization loss is computed based on the Mahalanobis distances between the novel classification weights and attractor vectors.

SUMMARY

[0013] According to one embodiment, a method is provided for continual few-shot learning. A model for a base task is generated with base classification weights for base classes of the base task. A series of novel tasks is sequentially received. Upon receiving each novel task in the series of novel tasks, the model is updated by a weight generator with novel classification weights for novel classes of the respective novel task. The novel classification weights are generated based on one or more of the base classification weights and, when one or more other novel tasks in the series are previously received, one or more other novel classification weights for novel classes of the one or more other novel tasks. Additionally, for each novel task, a first set of samples of the respective novel task are classified into the novel classes using the updated model.

[0014] According to one embodiment, a UE is provided that includes a processor and a non-transitory computer readable storage medium storing instructions. When executed, the instructions cause the processor to generate a model for a base task with base classification weights for base classes of the base task, and to sequentially receive a

series of novel tasks. The instructions also cause the processor to, upon receiving each novel task in the series of novel tasks, update the model with novel classification weights for the novel classes of the respective novel task. The novel classification weights are generated by a weight generator based on one or more of the base classification weights and, when one or more other novel tasks in the series are previously received, one or more other novel classification weights for novel classes of the one or more other novel tasks. The instructions further cause the processor to, upon receiving each novel task, classify a first set of samples of the respective novel task into the novel classes using the updated model.

BRIEF DESCRIPTION OF THE DRAWINGS

[0015] The above and other aspects, features, and advantages of certain embodiments of the present disclosure will be more apparent from the following detailed description, when taken in conjunction with the accompanying drawings, in which:

[0016] FIG. **1** is a diagram illustrating episodic few-shot learning;

[0017] FIG. **2** is a diagram illustrating few-shot learning without forgetting base classes;

[0018] FIG. **3** is a is a diagram illustrating an example of continual few-shot learning in three stages, according to an embodiment;

[0019] FIG. **4** is a flowchart illustrating a method for continual few-shot learning, according to an embodiment; and

[0020] FIG. **5** is a block diagram of an electronic device in a network environment, according to an embodiment.

DETAILED DESCRIPTION

[0021] Hereinafter, embodiments of the present disclosure are described in detail with reference to the accompanying drawings. It should be noted that the same elements will be designated by the same reference numerals although they are shown in different drawings. In the following description, specific details such as detailed configurations and components are merely provided to assist with the overall understanding of the embodiments of the present disclosure. Therefore, it should be apparent to those skilled in the art that various changes and modifications of the embodiments described herein may be made without departing from the scope of the present disclosure. In addition, descriptions of well-known functions and constructions are omitted for clarity and conciseness. The terms described below are terms defined in consideration of the functions in the present disclosure, and may be different according to users, intentions of the users, or customs. Therefore, the definitions of the terms should be determined based on the contents throughout this specification.

[0022] The present disclosure may have various modifications and various embodiments, among which embodiments are described below in detail with reference to the accompanying drawings. However, it should be understood that the present disclosure is not limited to the embodiments, but includes all modifications, equivalents, and alternatives within the scope of the present disclosure.

[0023] Although the terms including an ordinal number such as first, second, etc. may be used for describing various elements, the structural elements are not restricted by the terms. The terms are only used to distinguish one element from another element. For example, without departing from the scope of the present disclosure, a first structural element may be referred to as a second structural element. Similarly, the second structural element may also be referred to as the first structural element. As used herein, the term "and/or" includes any and all combinations of one or more associated items.

[0024] The terms used herein are merely used to describe various embodiments of the present disclosure but are not intended to limit the present disclosure. Singular forms are intended to include plural forms unless the context clearly indicates otherwise. In the present disclosure, it should be understood that the terms "include" or "have" indicate the existence of a feature, a number, a step, an operation, a structural element, parts, or a combination thereof, and do not exclude the existence or probability of the addition of one or more other features, numerals, steps, operations, structural elements, parts, or combinations thereof.

[0025] Unless defined differently, all terms used herein have the same meanings as those understood by a person skilled in the art to which the present disclosure belongs. Terms such as those defined in a generally used dictionary are to be interpreted to have the same meanings as the contextual meanings in the relevant field of art, and are not to be interpreted to have ideal or excessively formal meanings unless clearly defined in the present disclosure.

[0026] The electronic device according to one embodiment may be one of various types of electronic devices. The electronic devices may include, for example, a portable communication device (e.g., a smart phone), a computer, a portable multimedia device, a portable medical device, a camera, a wearable device, or a home appliance. According to one embodiment of the disclosure, an electronic device is not limited to those described above.

[0027] The terms used in the present disclosure are not intended to limit the present disclosure but are intended to include various changes, equivalents, or replacements for a corresponding embodiment. With regard to the descriptions of the accompanying drawings, similar reference numerals may be used to refer to similar or related elements. A singular form of a noun corresponding to an item may include one or more of the things, unless the relevant context clearly indicates otherwise. As used herein, each of such phrases as "A or B," "at least one of A and B," "at least one of A or B," "A, B, or C," "at least one of A, B, and C," and "at least one of A, B, or C," may include all possible combinations of the items enumerated together in a corresponding one of the phrases. As used herein, terms such as "1st," "2nd," "first," and "second" may be used to distinguish a corresponding component from another component, but are not intended to limit the components in other aspects (e.g., importance or order). It is intended that if an element (e.g., a first element) is referred to, with or without the term "operatively" or "communicatively", as "coupled with," "coupled to," "connected with," or "connected to" another element (e.g., a second element), it indicates that the element may be coupled with the other element directly (e.g., wired), wirelessly, or via a third element.

[0028] As used herein, the term "module" may include a unit implemented in hardware, software, or firmware, and may interchangeably be used with other terms, such as, for example, "logic," "logic block," "part," and "circuitry." A module may be a single integral component, or a minimum

unit or part thereof, adapted to perform one or more functions. For example, according to one embodiment, a module may be implemented in a form of an application-specific integrated circuit (ASIC).

[0029] Embodiments of the disclosure provide a framework for continual few-shot learning. Such a framework can be used in many applications to progressively learn new tasks (e.g., new classes, new objects, etc.), without forgetting the older tasks that have already been learned.

[0030] A model for a base task (having base classes) is pre-trained. The model for novel tasks (having novel classes) is then updated. For the novel tasks, it is assumed that only a few samples (e.g., 1 sample or 5 samples) are provided for each novel class, as in traditional few-shot learning. A base task T_0 is provided given base training set D_0. A series of N-way K-shot few shot learning tasks T_i are sequentially learned, given training sets D_i for i=1, 2, ...

[0031] The number of few-shot learning tasks is indefinite. Training set D_i is from a set of classes C_i such that $C_i \cap C_j = \phi$, $\forall i \neq j$.

[0032] For each task T_i, a model is updated with the only the current training set D_i. Data from past tasks cannot be revisited. However, in testing, the trained model is evaluated on all previous classes (i.e., $C_0 \cup C_1 \cup \ldots \cup C_i$).

[0033] Continual few-shot learning has a more practical usage than traditional few-shot learning in that the model remembers all learned classes when training data progressively arrives.

[0034] A more detailed description of the above-described continual few-shot learning steps is set forth below.

[0035] First, a feature extractor F_θ and a set of classification weight vectors $W_0=[w_c]_{c\in C_0}$ are pre-trained. For example, assuming linear classification after feature extraction, the inference (or testing) output y for input x is given by Equation (1) below:

$$\hat{y} = \underset{c\in C_0}{\operatorname{argmax}} \{w_c^T F_\theta(x)\} \tag{1}$$

[0036] After learning task T_i, inference is performed as set forth in Equation (2) below:

$$\hat{y} = \underset{c\in C_0 \cup C_1 \cup \ldots \cup C_i}{\operatorname{argmax}} \{w_c^T F_\theta(x)\} \tag{2}$$

All classes learned are of interest, and a set of classification weight vectors $W_i=[w_c]_{c\in C_0}$ for the novel classes C_i of task T_i are needed, given W_0, W_1, . . . , W_{i-1}.

[0037] In order to obtain the set of classification weight vectors W_i for the novel classes C_i, a weight generator utilizes the few-shot training set D_i and the classification weights for the previously learned classes (i.e., W_0, W_1, . . . , W_{i-1}). Specifically, where g_ϕ denotes the weight generator, and using the feature extractor output of the few-shot training set D_i, W_i is set forth in Equation (3) below:

$$W_i = g_\phi(F_\theta(D_i), W_0, W_1, \ldots, W_{i-1}) \tag{3}$$

[0038] Thus, in continual few-shot learning, the weight generator uses all previously learned classification weights as its input, as a series of few-shot tasks are progressively learned, to produce the classification weights for the novel class, rather than only using the base class weights, as in few-shot learning without forgetting base classes.

[0039] As the number of learned few-shot tasks increases, the number of classification weights that are provided to the above-described weight generator grows. Accordingly, two methods are provided for training the weight generator.

[0040] In a first method, the weight generator is optimized for a random number of new base classes. First, "fake" few-shot learning tasks are constructed from D_0. Specifically, the number of new base classes $\hat{C}_0$ is randomly selected (i.e., $N_0^{min} \leq |\hat{C}_0| \leq |C_0|$). "New" base classes $\hat{C}_0$ and "fake" novel classes $\hat{C}_1$ are randomly selected from the base classes C_0 (i.e., $\hat{C}_0 \cap \hat{C}_1 = \phi$, $|\hat{C}_1|=N$). K samples are randomly selected for each class of $\hat{C}_1$ and put in $\hat{S}_1$. The K samples are fed to the weight generator. Some samples are randomly selected for each class from $\hat{C}_0$ and $\hat{C}_1$, and put in $\hat{D}_0$ and $\hat{D}_1$, respectively. The randomly selected samples are used to calculate cross-entropy.

[0041] Optimization is performed in accordance with Equation (4) below:

$$\min_{W_0,\phi} E\left[E_{x,y\in \hat{D}_0\cup\hat{D}_1}\left[\text{CrossEntropy}\left(y, \text{softmax}\left(\left[\hat{W}_0, g_\phi(\hat{S}_1, \hat{W}_0)\right]^T F_\theta(x)\right)\right)\right]\right] \tag{4}$$

[0042] where $\hat{W}_0$ are the classification weight vectors in W_0 that correspond to $\hat{C}_0$.

[0043] In another embodiment, multiple weight generators are trained for random numbers of "new" base classes. Assuming that the number of base classes belongs to a fixed finite range (e.g., 50 to 100), a separate weight generate is trained for each random number of base classes. The weights of multiple weight generators are averaged to get one fused weight generator.

[0044] When the number of few-shot learning tasks that are added after the base model is arbitrary and is not pre-determined, it is difficult to optimize the weight generator for an arbitrary number of few-shot learning tasks. In a second method for training the weight generator, the number of few-shot learning tasks are limited (e.g., three) and the weight generator is trained to minimize the classification error over the fixed number of few-shot leaning tasks.

[0045] FIG. **3** is a diagram illustrating an example of continual few-shot learning in three stages, according to an embodiment. In a first stage, a model is trained for the base classes. Using base class weights **302** and a first set of novel class samples **304**, a weight generator **306** generates a first set of novel classification weights **308** for the first few-shot task. In a second stage, the classification weights for the base classes **302** and the generated first set of classification weights **308** are used by the weight generator **306** in combination with a second set of novel class samples **310** to generate a second set of classification weights **312** for the second few-shot learning task. In a third phase, the classifications weights for the base classes **302**, the generated first set of classification weights **308**, and the generated second set of classification weights **312** are used by the weight generator **306** in combination with a third set of novel class samples **314** to generate a third set of classification weights **316** for the third few-shot learning task.

[0046] This continual few-shot learning is performed a fixed number of times. In each stage, the loss that is used to

train the weight generator is defined as the cross-entropy loss for base classes and learned novel classes. The average classification loss for all stages is determined and the weight generator is optimized to minimize the average loss.

[0047] Specifically, with respect to the optimization of a weight generator for a fixed number of few-shot learning tasks, a number k of "fake" few-shot learning tasks are first constructed from D_0. Specifically, "new" base classes $\hat{C}_0$ and k sets of "fake novel classes $\hat{C}_1$, $\hat{C}_2$, . . . $\hat{C}_k$ are randomly selected from the base classes C_0, as set forth in Equation (5) below:

$$|\hat{C}_i|=N,\ 1\le i\le k,\ |\hat{C}_0|=|C_0|-kN,\ C_0=\cup_{i=0}^{k}\hat{C}_i,\hat{C}_i\cap\hat{C}_j=\phi,\ \forall i\neq j \tag{5}$$

[0048] K samples are randomly selected for each class of $\hat{C}_i$ of and put into $\hat{S}_i$ for $1\le i\le k$, respectively. The randomly selected K samples are fed to the weight generator. Some samples for each class are randomly selected from $\hat{C}_i$, and put into $\hat{D}_i$ for $0\le i\le k$, respectively. These randomly selected samples are used to calculate cross-entropy.

[0049] Optimization is performed in accordance with Equation (6) below:

$$\min_{W_0,\phi}\sum_{i=1}^{k}E\Big[E_{x,y\in\hat{D}_0\cup\hat{D}_1\cup\ldots\cup\hat{D}_i}\Big[\mathrm{CrossEntropy}\big(y,\mathrm{softmax}\big(\big[\hat{W}_0,\hat{W}_1,\ldots,\hat{W}_i\big]^T F_\theta(x)\big)\big)\Big]\Big] \tag{6}$$

where $W_i=g_\phi(S_i, W_0, W_1, \ldots, W_{i-1})$ and $\hat{W}_0$ are the classification weight vectors in W_0 that correspond to $\hat{C}_0$.

[0050] A first architecture for a weight generator includes a bi-attention weight generator. D_i^c is set as the data of class c in D_i. When $W_0^{i-1}=[W_0, W_1, \ldots, W_{i-1}]$, the classification weight w_c of class c yielded by the bi-attention weight generator is set forth in Equation (7) below:

$$w_c=\mathrm{mean}_{x\in D_i^c}\left(W_V W_0^{i-1}\mathrm{Att}(W_Q F_\theta(x), W_K W_0^{i-1})^T\right) \tag{7}$$

where W_Q, W_K, and W_V are linear transformation weights for query, key, and value of the bi-attention module, and

$$\mathrm{Att}(A,B)=\mathrm{softmax}\left(\frac{A^T B}{\sqrt{d}}\right)$$

[0051] A second architecture for a weight generator includes a self-attention weight generator, in which

$$W_{all}=\left[W_0^{i-1},\mathrm{mean}_{x\in D_i^{c_1}}(F_\theta(x)),\ldots,\mathrm{mean}_{x\in D_i^{c_N}}(F_\theta(x))\right],$$

for $c_1, \ldots, c_N\in C_i$. The classification weight yielded by the self-attention weight generator is set forth in Equation (8) below:

$$W_{all}\rightarrow W_V W_{all}Att(W_Q W_{all}, W_K W_{all})^T \tag{8}$$

where N_B is the number of base classes and X_n denotes the n-th column of X.

[0052] The self-attention weight generator differs from the bi-attention weight generator in that the base-class weights are updated in the self-attention weight generator.

[0053] The proposed weight generator modifications can be applied for the attention attractor network, having output that is used to regularize the weights (instead of generating the weights).

[0054] The bi-attention and self-attention weight generators can be modified to be a multi-head bi-attention weight generator and a multi-head self-attention weight generator, respectively.

[0055] Referring now to FIG. **4**, a flowchart illustrates a method for continual few-shot learning, according to an embodiment. A model for a base task is pre-trained with base classification weights for base classes of the base task, at **402**. The model includes a feature extractor. New base classes and fake novel classes are selected from the base classes, at **404**. An average cross-entropy loss is determined using randomly selected samples from each of the classes that are to be used to optimize a weight generator, at **406**. The weight generator is optimized, at **408**, using a random number of the new base classes and a fake novel task of the fake novel classes, or using a fixed number of fake novel tasks of the fake novel classes.

[0056] A novel task in a series of novel tasks is received, at **410**. Features are extracted from a set of samples of the novel task, at **412**. The set of samples are pre-classified into novel classes, which are different from the base classes.

[0057] Novel classification weights for the novel classes are generated, at **414**. For example, the novel classification weights may be generated, by the weight generator, using the extracted features, the base classification weights, and one or more other novel classification weights. The one or more other novel classifications weights are for novel classes of one or more other novel tasks in the series that are previously received. A number of the one or more other novel tasks may be less than or equal to three.

[0058] As another example, the novel classification weights may be generated, by the weight generator, using the extracted features and classification weights of classes selected from the base classes and the novel classes of the one or more other novel tasks in the series that are previously received. For each novel task, a random number of classes may be selected for the classification weights in generating the novel classification weights.

[0059] The model is updated with the novel classification weights for the novel classes of the novel task, at **416**.

[0060] A set of unclassified samples of the novel task are classified into the novel classes using the updated model, at **418**. At **420** is determined whether another novel task in the series of novel tasks is to be received. When another novel task is to be received, the methodology returns to **410**. When another novel task is not to be received, the methodology terminates at **422**.

[0061] FIG. **5** is a block diagram of an electronic device in a network environment, according to one embodiment. Referring to FIG. **5**, an electronic device **501** in a network environment **500** may communicate with an electronic device **502** via a first network **598** (e.g., a short-range wireless communication network), or an electronic device **504** or a server **508** via a second network **599** (e.g., a long-range wireless communication network). The electronic device **501** may communicate with the electronic device **504** via the server **508**. The electronic device **501**

may include a processor **520**, a memory **530**, an input device **550**, a sound output device **555**, a display device **560**, an audio module **570**, a sensor module **576**, an interface **577**, a haptic module **579**, a camera module **580**, a power management module **588**, a battery **589**, a communication module **590**, a subscriber identification module (SIM) **596**, or an antenna module **597**. In one embodiment, at least one (e.g., the display device **560** or the camera module **580**) of the components may be omitted from the electronic device **501**, or one or more other components may be added to the electronic device **501**. Some of the components may be implemented as a single integrated circuit (IC). For example, the sensor module **576** (e.g., a fingerprint sensor, an iris sensor, or an illuminance sensor) may be embedded in the display device **560** (e.g., a display).

[0062] The processor **520** may execute, for example, software (e.g., a program **540**) to control at least one other component (e.g., a hardware or a software component) of the electronic device **501** coupled with the processor **520**, and may perform various data processing or computations. As at least part of the data processing or computations, the processor **520** may load a command or data received from another component (e.g., the sensor module **576** or the communication module **590**) in volatile memory **532**, process the command or the data stored in the volatile memory **532**, and store resulting data in non-volatile memory **534**. The processor **520** may include a main processor **521** (e.g., a central processing unit (CPU) or an application processor (AP)), and an auxiliary processor **523** (e.g., a graphics processing unit (GPU), an image signal processor (ISP), a sensor hub processor, or a communication processor (CP)) that is operable independently from, or in conjunction with, the main processor **521**. Additionally or alternatively, the auxiliary processor **523** may be adapted to consume less power than the main processor **521**, or execute a particular function. The auxiliary processor **523** may be implemented as being separate from, or a part of, the main processor **521**.

[0063] The auxiliary processor **523** may control at least some of the functions or states related to at least one component (e.g., the display device **560**, the sensor module **576**, or the communication module **590**) among the components of the electronic device **501**, instead of the main processor **521** while the main processor **521** is in an inactive (e.g., sleep) state, or together with the main processor **521** while the main processor **521** is in an active state (e.g., executing an application). The auxiliary processor **523** (e.g., an image signal processor or a communication processor) may be implemented as part of another component (e.g., the camera module **580** or the communication module **590**) functionally related to the auxiliary processor **523**.

[0064] The memory **530** may store various data used by at least one component (e.g., the processor **520** or the sensor module **576**) of the electronic device **501**. The various data may include, for example, software (e.g., the program **540**) and input data or output data for a command related thereto. The memory **530** may include the volatile memory **532** or the non-volatile memory **534**.

[0065] The program **540** may be stored in the memory **530** as software, and may include, for example, an operating system (OS) **542**, middleware **544**, or an application **546**.

[0066] The input device **550** may receive a command or data to be used by another component (e.g., the processor **520**) of the electronic device **501**, from the outside (e.g., a user) of the electronic device **501**. The input device **550** may include, for example, a microphone, a mouse, or a keyboard.

[0067] The sound output device **555** may output sound signals to the outside of the electronic device **501**. The sound output device **555** may include, for example, a speaker or a receiver. The speaker may be used for general purposes, such as playing multimedia or recording, and the receiver may be used for receiving an incoming call. The receiver may be implemented as being separate from, or a part of, the speaker.

[0068] The display device **560** may visually provide information to the outside (e.g., a user) of the electronic device **501**. The display device **560** may include, for example, a display, a hologram device, or a projector and control circuitry to control a corresponding one of the display, hologram device, and projector. The display device **560** may include touch circuitry adapted to detect a touch, or sensor circuitry (e.g., a pressure sensor) adapted to measure the intensity of force incurred by the touch.

[0069] The audio module **570** may convert a sound into an electrical signal and vice versa. The audio module **570** may obtain the sound via the input device **550**, or output the sound via the sound output device **555** or a headphone of an external electronic device **502** directly (e.g., wired) or wirelessly coupled with the electronic device **501**.

[0070] The sensor module **576** may detect an operational state (e.g., power or temperature) of the electronic device **501** or an environmental state (e.g., a state of a user) external to the electronic device **501**, and then generate an electrical signal or data value corresponding to the detected state. The sensor module **576** may include, for example, a gesture sensor, a gyro sensor, an atmospheric pressure sensor, a magnetic sensor, an acceleration sensor, a grip sensor, a proximity sensor, a color sensor, an infrared (IR) sensor, a biometric sensor, a temperature sensor, a humidity sensor, or an illuminance sensor.

[0071] The interface **577** may support one or more specified protocols to be used for the electronic device **501** to be coupled with the external electronic device **502** directly (e.g., wired) or wirelessly. The interface **577** may include, for example, a high definition multimedia interface (HDMI), a universal serial bus (USB) interface, a secure digital (SD) card interface, or an audio interface.

[0072] A connecting terminal **578** may include a connector via which the electronic device **501** may be physically connected with the external electronic device **502**. The connecting terminal **578** may include, for example, an HDMI connector, a USB connector, an SD card connector, or an audio connector (e.g., a headphone connector).

[0073] The haptic module **579** may convert an electrical signal into a mechanical stimulus (e.g., a vibration or a movement) or an electrical stimulus which may be recognized by a user via tactile sensation or kinesthetic sensation. The haptic module **579** may include, for example, a motor, a piezoelectric element, or an electrical stimulator.

[0074] The camera module **580** may capture a still image or moving images. The camera module **580** may include one or more lenses, image sensors, image signal processors, or flashes.

[0075] The power management module **588** may manage power supplied to the electronic device **501**. The power management module **588** may be implemented as at least part of, for example, a power management integrated circuit (PMIC).

[0076] The battery **589** may supply power to at least one component of the electronic device **501**. The battery **589** may include, for example, a primary cell which is not rechargeable, a secondary cell which is rechargeable, or a fuel cell.

[0077] The communication module **590** may support establishing a direct (e.g., wired) communication channel or a wireless communication channel between the electronic device **501** and the external electronic device (e.g., the electronic device **502**, the electronic device **504**, or the server **508**) and performing communication via the established communication channel. The communication module **590** may include one or more communication processors that are operable independently from the processor **520** (e.g., the AP) and supports a direct (e.g., wired) communication or a wireless communication. The communication module **590** may include a wireless communication module **592** (e.g., a cellular communication module, a short-range wireless communication module, or a global navigation satellite system (GNSS) communication module) or a wired communication module **594** (e.g., a local area network (LAN) communication module or a power line communication (PLC) module). A corresponding one of these communication modules may communicate with the external electronic device via the first network **598** (e.g., a short-range communication network, such as Bluetooth™, wireless-fidelity (Wi-Fi) direct, or a standard of the Infrared Data Association (IrDA)) or the second network **599** (e.g., a long-range communication network, such as a cellular network, the Internet, or a computer network (e.g., LAN or wide area network (WAN)). These various types of communication modules may be implemented as a single component (e.g., a single IC), or may be implemented as multiple components (e.g., multiple ICs) that are separate from each other. The wireless communication module **592** may identify and authenticate the electronic device **501** in a communication network, such as the first network **598** or the second network **599**, using subscriber information (e.g., international mobile subscriber identity (IMSI)) stored in the subscriber identification module **596**.

[0078] The antenna module **597** may transmit or receive a signal or power to or from the outside (e.g., the external electronic device) of the electronic device **501**. The antenna module **597** may include one or more antennas, and, therefrom, at least one antenna appropriate for a communication scheme used in the communication network, such as the first network **598** or the second network **599**, may be selected, for example, by the communication module **590** (e.g., the wireless communication module **592**). The signal or the power may then be transmitted or received between the communication module **590** and the external electronic device via the selected at least one antenna.

[0079] At least some of the above-described components may be mutually coupled and communicate signals (e.g., commands or data) therebetween via an inter-peripheral communication scheme (e.g., a bus, a general purpose input and output (GPIO), a serial peripheral interface (SPI), or a mobile industry processor interface (MIPI)).

[0080] Commands or data may be transmitted or received between the electronic device **501** and the external electronic device **504** via the server **508** coupled with the second network **599**. Each of the electronic devices **502** and **504** may be a device of a same type as, or a different type, from the electronic device **501**. All or some of operations to be executed at the electronic device **501** may be executed at one or more of the external electronic devices **502**, **504**, or **508**. For example, if the electronic device **501** should perform a function or a service automatically, or in response to a request from a user or another device, the electronic device **501**, instead of, or in addition to, executing the function or the service, may request the one or more external electronic devices to perform at least part of the function or the service. The one or more external electronic devices receiving the request may perform the at least part of the function or the service requested, or an additional function or an additional service related to the request, and transfer an outcome of the performing to the electronic device **501**. The electronic device **501** may provide the outcome, with or without further processing of the outcome, as at least part of a reply to the request. To that end, a cloud computing, distributed computing, or client-server computing technology may be used, for example.

[0081] One embodiment may be implemented as software (e.g., the program **540**) including one or more instructions that are stored in a storage medium (e.g., internal memory **536** or external memory **538**) that is readable by a machine (e.g., the electronic device **501**). For example, a processor of the electronic device **501** may invoke at least one of the one or more instructions stored in the storage medium, and execute it, with or without using one or more other components under the control of the processor. Thus, a machine may be operated to perform at least one function according to the at least one instruction invoked. The one or more instructions may include code generated by a complier or code executable by an interpreter. A machine-readable storage medium may be provided in the form of a non-transitory storage medium. The term "non-transitory" indicates that the storage medium is a tangible device, and does not include a signal (e.g., an electromagnetic wave), but this term does not differentiate between where data is semi-permanently stored in the storage medium and where the data is temporarily stored in the storage medium.

[0082] According to one embodiment, a method of the disclosure may be included and provided in a computer program product. The computer program product may be traded as a product between a seller and a buyer. The computer program product may be distributed in the form of a machine-readable storage medium (e.g., a compact disc read only memory (CD-ROM)), or be distributed (e.g., downloaded or uploaded) online via an application store (e.g., Play Store™), or between two user devices (e.g., smart phones) directly. If distributed online, at least part of the computer program product may be temporarily generated or at least temporarily stored in the machine-readable storage medium, such as memory of the manufacturer's server, a server of the application store, or a relay server.

[0083] According to one embodiment, each component (e.g., a module or a program) of the above-described components may include a single entity or multiple entities. One or more of the above-described components may be omitted, or one or more other components may be added. Alternatively or additionally, a plurality of components (e.g., modules or programs) may be integrated into a single component. In this case, the integrated component may still perform one or more functions of each of the plurality of components in the same or similar manner as they are performed by a corresponding one of the plurality of components before the integration. Operations performed by the

module, the program, or another component may be carried out sequentially, in parallel, repeatedly, or heuristically, or one or more of the operations may be executed in a different order or omitted, or one or more other operations may be added.

[0084] Although certain embodiments of the present disclosure have been described in the detailed description of the present disclosure, the present disclosure may be modified in various forms without departing from the scope of the present disclosure. Thus, the scope of the present disclosure shall not be determined merely based on the described embodiments, but rather determined based on the accompanying claims and equivalents thereto.

What is claimed is:

1. A method for continual few-shot learning, comprising:

generating a model for a base task with base classification weights for base classes of the base task;

sequentially receiving a series of novel tasks; and

upon receiving each novel task in the series of novel tasks:

updating the model with novel classification weights for novel classes of the respective novel task, wherein the novel classification weights are generated by a weight generator based on one or more of the base classification weights and, when one or more other novel tasks in the series are previously received, one or more other novel classification weights for novel classes of the one or more other novel tasks; and

classifying a first set of samples of the respective novel task into the novel classes using the updated model.

2. The method of claim **1**, further comprising training the weight generator using a random number of the base classes and a fake novel task of fake novel classes selected from the base classes, or using a fixed number of fake novel tasks of the fake novel classes selected from the base classes.

3. The method of claim **2**, wherein training the weight generator comprises determining an average cross-entropy loss using randomly selected samples from classes used to train the weight generator.

4. The method of claim **1**, wherein the model comprises a feature extractor.

5. The method of claim **1**, wherein each novel task further comprises a second set of samples that are classified into novel classes.

6. The method of claim **5**, wherein updating the model comprises:

extracting features from the second set of samples of the respective novel task; and

generating the novel classification weights by the weight generator using the extracted features, the base classification weights, and the other novel classification weights.

7. The method of claim **6**, wherein a number of the one or more other novel tasks is less than or equal to three.

8. The method of claim **5**, wherein updating the model comprises:

extracting features from the second set of samples of the respective novel task; and

generating the novel classification weights by the weight generator using the extracted features and classification weights of classes selected from the base classes and the novel classes of the one or more other novel tasks.

9. The method of claim **8**, wherein, for each novel task, a random number of the classes is selected for the classification weights that are used to generate the novel classification weights.

10. The method of claim **1**, wherein the weight generator is a bi-attention weight generator or a self-attention weight generator.

11. A user equipment (UE) comprising:

a processor; and

a non-transitory computer readable storage medium storing instructions that, when executed, cause the processor to:

generate a model for a base task with base classification weights for base classes of the base task;

sequentially receive a series of novel tasks; and

upon receiving each novel task in the series of novel tasks:

update the model with novel classification weights for novel classes of the respective novel task, wherein the novel classification weights are generated by a weight generator based on one or more of the base classification weights and, when one or more other novel tasks in the series are previously received, one or more other novel classification weights for novel classes of the one or more other novel tasks; and

classify a first set of samples of the respective novel task into the novel classes using the updated model.

12. The UE of claim **11**, wherein the processor is further configured to train the weight generator using a random number of the base classes and a fake novel task of fake novel classes selected from the base classes, or using a fixed number of fake novel tasks of fake novel classes selected from the base classes.

13. The UE of claim **12**, wherein, in training the weight generator, the processor is further configured to determine an average cross-entropy loss using randomly selected samples from classes used to train the weight generator.

14. The UE of claim **11**, wherein the model comprises a feature extractor.

15. The UE of claim **11**, wherein each received novel task further comprises a second set of samples that are classified into novel classes.

16. The UE of claim **15**, wherein, in updating the model, the processor is further configured to:

extract features from the second set of samples of the respective novel task; and

generate the novel classification weights by the weight generator using the extracted features, the base classification weights, and the other novel classification weights.

17. The UE of claim **16**, wherein a number of the one or more other novel tasks is less than or equal to three.

18. The UE of claim **15**, wherein, in updating the model, the processor is further configured to:

extract features from the second set of samples of the respective novel task; and

generate the novel classification weights by the weight generator using the extracted features and classification weights of classes selected from the base classes and the novel classes of the one or more other novel tasks.

19. The UE of claim **18**, wherein, for each novel task, a random number of the classes is selected for the classification weights that are used to generate the novel classification weights.

20. The UE of claim **11**, wherein the weight generator is a bi-attention weight generator or a self-attention weight generator.

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